A new ETF Landscape and its Relationship to the Volatility of its Underlying Assets

An empirical study of the S&P 500

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Abstract

The global market for exchange traded funds (ETFs) has during the last decade sustained substantial growth. A global increase of AUM from ~400 billion USD in 2005 to above 7.7 trillion USD in 2020 has brought with it a changed landscape. With an anchor in prominent literature, jointly indicating that ETFs have inadvertent consequences on their underlying securities, we study the relationship between ETFs and volatility of the underlying assets through estimated regression models. Examining data on the constituents of the S&P 500 for a previously uninvestigated period of five years, we find no positive correlation between increased ETF ownership and volatility, contrasting previous findings. Additionally, we provide novel insight through dissecting our set of ETFs into distinct categories, studying their separate effects. Our results indicate that effects and magnitude differ depending on the ETF category, with varying significance.

Keywords

ETF, Volatility, Arbitrage, Shock Propagation, Index Investing

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List of Abbreviations

APs	Authorized Participants
AUM	Assets Under Management
C/R	Creation & Redemption
ETFs	Exchange Traded Funds
HFT	High-Frequency-Trading
ICI	Investment Company Institute
LETFs	Leveraged and Inverse Exchange Traded Funds
NAV	Net Asset Value
PTM	Past-12-Month Return
VWAP	Volume Weighted Average Price

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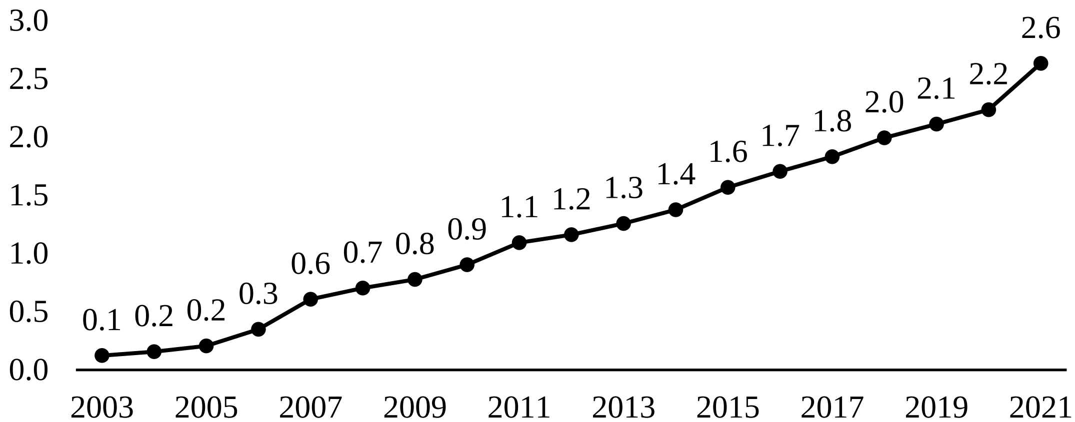
1. Introduction

1.1 Background

Exchange traded funds (ETFs) have during the last decade experienced tremendous growth. With a worldwide increase in quantity of 3,000% between 2003 and 2021, and an increase of AUM for global funds from 417 billion USD in 2005 to above 7.7 trillion USD in 2020, investors seem to cherish the liquidity and diversification benefits the funds occupy. North America stands for a 74% share of the global ETF AUM, and 2,204 of the world's 7,602 ETFs are located in the US, making it the most prominent region for ETFs in terms of size. In 2019, the US experienced the strongest fund flow to ETFs, which was approximately 2.6x larger than the second strongest which was Europe. In terms of the held asset classes of American ETFs, equities stand for a vast majority representing ~70% (Statista, 2022).

Figure 1
Number of ETFs on the U.S. market, 2003-2021 (Thousands)



Source: ETFGI (2022)

For investors, ETFs are most commonly used to speculate, hedge positions, or gain arbitrage in cases where the law of one price is violated. As opposed to many other basket securities such as mutual funds and traditional index funds, ETFs can satisfy a high-frequency trade demand through intraday liquidity. Like stocks, they are continuously traded on an exchange, to the convenience of those seeking liquidity and exposure to a specific industry or set of assets. Their existence also widens the general trading possibilities. ETFs can be short- sold and baskets can include securities that are typically hard to acquire a position in, especially by retail investors, and may for example comprise of stock in emerging markets or high-yield corporate bonds. Because the realized capital gains throughout the holding period of an ETF is lower than for similar investment products due to the reinvestment of dividends, they offer tax advantages over, for example, mutual funds. ETFs also possess relatively low investment costs, which by financial institutions is considered the most attractive attribute (Statista, 2022).

The increased presence of ETFs has led to an abundance of research on their implications on the general market and its participants. Apart from affecting trading dynamics and providing investors with a wider set of possibilities, prominent research indicates that ETFs may have a significant impact on the attributes of the underlying assets, with equity being the most studied asset class. Price-efficiency, volatility, co-movement and shock propagation are all aspects that recent researchers have set out to study. Though the presence of ETFs at first glance may appear as solely providing benefits for market participants, a vast amount of research indicates inadvertent consequences for the securities in the ETF portfolios. Ben-David, Franzoni and Moussawi (2018) develop a model illustrating how liquidity shocks caused by high-frequency demand, which ETFs tend to attract, has an effect on the price of the underlying asset, as an ETF and its portfolio are tied together by arbitrage. Shocks may therefore propagate to the underlying securities leading to increased volatility. Recent research on ETFs has found a positive correlation between volatility and ETF ownership in the U.S market. Both the primary and secondary market have been found to have a significant effect on the portfolio companies.

Building upon this research, we examine the relationship between ETF ownership and volatility of the underlying securities in the S&P 500 in a hitherto unexamined time period. Furthermore, we extend the existing literature by separating the ETFs into distinct categories depending on their investment style, and study their effects separately.

1.2 The Mechanics of ETFs

An ETF is an investment vehicle which commonly has the purpose of tracking a specific index (for example the S&P500 or the OMXS30) in a manner comparable to mutual index funds. Though it is common for an ETF to track an index, they vary widely in investment strategy. Similarly to mutual funds, they can for example focus on specific industries or sectors, or use leverage and derivatives to amplify returns of the underlying asset.

However, ETFs come with several key differences which distinguish them from mutual funds. ETFs are tradeable throughout the day during regular hours just as stocks, whereas mutual funds only trade end-of-day after the market closes, making ETFs much more relevant for high-frequency-trading (HFT). Mutual funds hold the underlying assets directly meaning that when it has received a net inflow of investments at the end of the trading day, the fund directly purchases additional stock. When it comes to ETFs, the procedure differs. While ETFs also hold a portfolio of securities, they do not engage in the buying and selling process directly themselves - this is instead done by selected Authorized Participants (APs). APs are typically large banks such as JPMorgan Chase or Goldman Sachs, that engage in the capital markets on the ETF's behalf. The ETF issues/redeems shares with the APs in blocks called "creation units" in exchange for a basket of securities or cash. The process is called the creation/redemption process (C/R process). "Creation" is the practice in which the ETF increases the number of shares outstanding, and "redemption" is the opposite - when the number of ETF shares outstanding is decreased. The C/R process takes place at the end of day after the exchange closes.

The function of APs is partly, as described above, to provide liquidity for the ETF, adjusting the number of shares in the ETF by providing or redeeming shares of the underlying securities. Another function of the APs is to correct the difference between the fund's Net Asset Value (NAV) and its market capitalization. Through the C/R process, the APs hence also act as intraday arbitrageurs. The arbitrage relationship between the NAV and market capitalization is fundamental to some of the inadvertent effects the ETFs have been indicated to have on the underlying asset. A more detailed explanation of how the mechanics of ETFs may affect the volatility of the underlying asset can be found in the third section under Hypothesis Development.

1.3 Relevance

Considering their rise, ETFs will likely play a central role in the future of investing and saving. It is hence crucial to examine and understand potential effects they may have on their underlying securities, and what broader implications that may have on the market. Though an abundance of related literature exists, the subject of ETFs has gained academic attention relatively recently, and conclusions differ and, in some cases, even contrast each other. This thesis contributes to the ongoing debate on the effects of ETFs on the underlying stock. The panel data covers a period that, to the best of our knowledge, has yet to be examined. Further on, the paper extends previous research through dissecting the set of ETFs into categories, studying potential divergences between them. Whilst the bulk of ETFs are passive index-tracking funds, other types of ETFs, such as sector niched and leveraged funds, have grown at a strong rate and literature suggests that different funds may affect the underlying stocks in diverse ways.

1.4 Method

Firstly, we define and extract a specific set of ETFs that track or have exposure to the S&P 500. The sample is limited to ETFs that are listed on US exchanges and contains 282 separate ETFs. We then collect their portfolio compositions and calculate the accumulated ownership in the S&P 500. This is done on a quarterly basis and yields a trend of growing ownership in the index.

To examine the volatility impact of ETF ownership, we then gather high frequency stock-level data on the constituent companies of the S&P 500. We also retrieve relevant control variables, which include skewness, logged market capitalization, inverse share price, Amihud ratio, price-to-book ratio, and PTM returns. All these metrics are computed using data from S&P Capital IQ and are discussed in more detail in the 'Data' section. Before subsequently performing regressions, we limit the extreme values and their potentially spurious effect through winsorizing our data at the 1% and 99% level.

We first examine the potential effect of ETF ownership in its entirety, meaning we utilize the complete set of ETFs, on the volatility of their portfolio equities through performing an OLS regression. We find contradicting results to those of closely related research published in leading journals, with Ben-David et al. (2018) being the most comparable with regards to method and data. As opposed to finding a relatively strong positive correlation between increased ETF ownership and volatility, we instead, with high significance, find a small negative correlation between the two variables. To increase the robustness of these findings, we perform two additional regressions with the same data set – one with time fixed effects and one with both firm and time fixed effects. The regression only controlling for time effects yields similar output to our first regression – we find an even stronger negative relationship between ETF ownership and volatility. This regression is also statistically significant. However, including both firm and monthly fixed effects, the relationship between the two becomes statistically insignificant, suggesting the previously established positive correlation, as found by e. g. Ben David et. al (2018) does not hold during the time period we examine.

Having established these differing findings for our sample, we examine reasons for the divergency through a granularization of ETFs on the category level. Separately studying the effects of the separate groups of ETFs provides novel insight into the ETF market, and may help explain our findings. Thus, we dissect the set of ETFs into four distinct categories - 'Core ETFs' (Core), 'Industry ETFs' (Industry), 'Leveraged ETFs' (Leveraged) and 'Other ETFs' (Other). Core includes funds that track a broader index. In the Industry category, we place funds that invest in certain sectors, e. g. real estate, financial services or telecommunications. Leveraged translates to funds promising a daily return multiple greater than 1, while Other includes all other ETFs, for example High-Dividend ETFs and Growth ETFs. We then run separate regressions for these distinct categories, examining potential differences in the degree of effect on volatility.

Our separate regressions for the individual ETF categories yield varying relationships with varying significance. Without fixed effects, Core and Industry ETF ownership both negatively correlate with volatility, at a 1% significance level. On the other hand, the remaining two ETF categories, Leveraged and Other, show a positive correlation with volatility. The Leveraged regression shows significance at the 10% level, whilst the Other regression is not statistically significant. However, including fixed effects, only one out of the four regressions show statistically significant results – the Other category maintains a positive ETF ownership coefficient with statistical significance.

The structure of the remainder of our thesis is as follows: The final part of the first section provides an overview of our scope. The second section comprises a literature review of relevant related research, and is followed by a third section which aims to develop the hypothesis through a discussion of the underlying concepts and recent market developments that underlines the relevance of the topic. In the fourth section, we explain the collection, cleaning and processing of the data. The fifth section presents our results which, in the following sixth section, are analyzed. The seventh and final section includes our last remarks, suggests directions for future research and concludes the thesis.

1.5 Scope

The US ETF market is by far the largest and most active in terms of fund flows. Though other markets have experienced considerable growth in the last decade, with the number of ETFs listed on Euronext growing from 631 to 1,289 between 2014 and 2020 for example (Statista, 2022), the US market is more mature. Size and maturity play a principal role in being able to study and determine the effect of a phenomena. Not only in terms of actual impact, but also in regard to practical factors, such as access to sufficiently large sets of data for findings to be statistically significant. The relative infancy of Europe, and especially the Nordics, poses a risk for lack of manifested effects, as studied effects of ETFs seem to increase with size and activity. Hence, this thesis exclusively studies the American stock market. More specifically, the data set comprises the S&P 500 as of 27th of February 2022 and a defined set of ETFs tracking one or more of these securities. We study a previously unexamined period spanning over five years, from January 2015 to January 2020. This period was spared from major crises and shocks to the equity markets, which mitigates the adverse effects a stock market crash may have on the results and its significance.

Primarily due to data issues, we decided not to study the primary market in terms of C/R flows and intraday volatility. The primary market and its effect have quite extensively been studied in several recent papers on ETFs (e. g Ben-David et al. (2018) and Brown, Davies and Ringgenberg (2021)).

2. Literature Review

In a broad sense, this thesis relates to the effect of derivatives on the idiosyncrasy and transparency of the underlying securities' prices. This long-running debate was first, to the best of our knowledge, formally introduced to academia by Stein (1987), who argued that imperfectly informed speculation in futures markets risks destabilizing spot prices. Grossman (1988) subsequently found evidence for futures improving price efficiency. The literature on ETFs and their inadvertent effects on the underlying assets has yet to reach any definite consensus. This thesis more specifically relates to the literature on ETFs' impact on their basket-securities' in terms of volatility. Through centering on this theme, we indirectly study the impact of ETFs on market quality and efficiency. Our thesis is also peripheral to the strands of literature on the effect of indexing on the market and propagation of non-fundamental demand shocks. The following literature review hence focuses on research on ETFs and their consequences for the market and its' participants.

A strand of literature from the mid 2010s shows that institutions play a role in non-fundamental demand shocks being impounded into asset prices due to flows from their investors. This strand especially looks at the effects caused by mutual funds. Antón and Polk (2014) show that institutional connectedness (connecting funds through common fund ownership) helps to predict cross-sectional variation in co-movement. They illustrate the implications of their findings through a trading strategy based on exploiting the price pressure induced by common ownership that uses the connected return as a signal of under or overvaluation. Basak and Pavlova (2013) reveals that institutional investors, through typical portfolio compositions, increase stock market volatility and create excess correlations among stocks belonging to an index.

Our thesis is rooted in the theme of passive index investing and its consequences on the market, as index-tracking ETFs constitute a majority of the ETF market. The capital allocated to index investing has grown by trillions of dollars (Bogle (2016)) in the last couple of decades. However, academia provides no consensus on the effect of investor composition on market efficiency. For example, Barush and Zhang (2021) and Bond and Garcia (2019) argue that increased presence of index investors reduces price informativeness. On the other hand, other literature (e. g. Grossman and Stiglitz (1980)) utilizing a different class of models, indicates that investor composition does not affect price efficiency in equilibrium. Another body of literature on index investing suggests that increased passive index ownership is associated with greater public scrutiny and enhanced corporate governance (Boone and White, 2015; Appel, Gormley and Keim, 2016). Adding a stock to an index has, by the large body of literature on stock co-movement, been found to affect its price (Kaul, Mehrotra and Morck, 2002; Wurgler and Zhuravskaya. 2002). Studying the S&P 500, Barberis, Shleifer and Wurgler (2005) and Goetzmann & Massa (2003), also show it increases correlation between stocks in the fund portfolio. This literature jointly indicates that non-fundamental factors are drivers of co-movement, and index compositions.

The ETF niche of the literature on index investing has grown considerably during the last decade, in line with the increased presence of ETFs. Through focusing on the increased presence of ETFs, Israeli, Lee and Sridharan (2017) investigate how the consequently changed composition of a firm's investor base affects the price efficiency of shares. While several studies find support for that ETF-arbitrage trading can facilitate intraday price discovery for the portfolio companies (Xu and Yin, 2017a; Bhattacharya and O'Hara, 2018; Xu, Yin and Zhao 2018; Buckle, Chen, Guo and Tong, 2018) suggesting that ETFs improves market efficiency, Israeli et al. (2017) comes to a contrasting conclusion and finds that increased ETF ownership can lead to (1) higher trading costs due to less liquidity and greater gap between bid-ask and (2) lower benefits from information acquisition (less pricing efficiency due to higher transaction costs) for the basket securities, which in combination ultimately results in less informative stock prices.

A considerable amount of research on ETFs' impact on the underlying assets concludes that their findings are, to different extents, a consequence of the arbitrage relationship between them. Da and Shive (2018) find that ETF ownership is associated with higher co-movement of the underlying securities. Arbitrageurs, who are otherwise enforcers of price efficiency, can in the case of ETFs instead contribute to excess co-movement. Agarwal, Hanouna, Moussawi and Stahel (2018) finds that ETF ownership exacerbates the correlation in liquidity of the underlying equities due them being tied by the law of one price, and the article shows that the underlying arbitrage mechanism correcting the deviation between the prices of the ETFs and its underlying stocks is the driver behind this.

Through specifically highlighting the arbitrage link between ETFs and their portfolio, and illustrating how price pressure from ETF flows and arbitrage activity increases volatility in the underlying assets, Ben-David et al. (2018) broke new ground. The paper shows that institutional investors trade ETFs more frequently than stocks, supporting the notion that ETFs are a catalyst for short-horizon traders. It further illustrates how the demand of this clientele of high-turnover investors is passed on to the underlying securities through the arbitrage channels. Brown et al. (2021) builds upon this using the ETF primary market to study non-fundamental demand and examining how signals for non-fundamental demand shocks can be observed through ETF flows. As these shocks have considerable effects on asset prices, APs correct these violations of the law of one price. Brown et al. (2021) provides evidence of APs generating excess returns in accordance with distorted asset prices in relation to their fundamental value. Both Brown et al. (2021) and Ben-

David et al (2018) contribute to the question of ETFs' effect on asset prices. That is, whether ETFs increase stock price accuracy or add more noise.

Building upon precedent papers, Malamud (2015) proposed a model in which ETFs can affect volatility through the liquidity shock transmission channel as well as through the time-varying risk premiums that investors require as compensation for taking on exposure to these shocks - both claims are consistent with the empirical evidence of Ben-David et al. (2018). Furthermore, Malamud found that the introduction of new ETFs may offset the negative effects of existing ETFs through a demand substitution effect, if the newly introduced ETFs are properly designed. They may function as a substitute for part of the demand of already existing ETFs resulting in a liquidity improvement, reducing volatility and commonality of the securities.

As opposed to Ben-David et al. (2018), whose paper the first section of this thesis aims to replicate, we include leveraged ETFs in our dataset, while also studying them as a separate group. The portfolio compositions of leveraged ETFs naturally differ from traditional ETF portfolios. Through using debt and derivatives, these funds amplify the returns of the underlying and aim to provide a daily return based on a multiple of a market index or other benchmark. The literature on leveraged ETFs is relatively scarce. Charupat and Miu (2011) presents evidence on leveraged ETFs containing both large premiums and discounts, which can increase market volatility. Tuzun (2014) also studies leveraged as well as inverse ETFs (LETFs) and finds that the rebalancing process likely was a contributor to stock market volatility during the 2008 crisis. However, both Trainor (2010), studying the American market, and Kim, Kang and Lee (2015), studying the Korean market, were unable to find any evidence that leveraged ETFs generate any additional market volatility.

Our hypothesis is based on, and aims to contribute to and extend, the aforementioned literature. The rationale behind it is derived and discussed in the next section.

3. Hypothesis Development

Evident from their increased presence is that ETFs will play a central role in the future of investing and saving. It is hence crucial to examine and understand if and how they affect the market, for example in terms of prices and volatility. Our main testable hypothesis is that increased ETF ownership will increase the volatility of the underlying equities in the S&P 500. We also hypothesize that ETF ownership affects volatility to different degrees, depending on the ETF type, as the ETF and its investor base may behave differently.

The recent literature on ETFs indicates that both the primary and secondary market activity have an effect on volatility of the underlying securities. The secondary ETF market can increase volatility in the underlying assets through more efficient and rapid price incorporation of new information. This presents investors with relatively frequent arbitrage opportunities as a result of discrepancies between the NAV of the ETF and the accumulated value of the underlying assets. These discrepancies are also eliminated in the primary market by APs through the C/R process. Consequently, liquidity shocks directed towards an ETF could, through these arbitrage channels, propagate onto their underlying assets and cause price movements. To illustrate this, let us presume that the demand for a specific ETF share rises. The increased demand leads to high amounts of buy orders, which increases the ETF share's price. As earlier explained, the difference between the NAV and market price will be corrected by arbitrageurs, who will buy the underlying assets and short the ETF. Naturally, this will increase the price of the underlying assets until the law of one price is enforced. Liquidity shocks that propagate in the described manner should have a larger impact and be more common for a stock when the ETF ownership in it is larger.

The ETF market exhibits high growth, and ETF ownership in the S&P 500 has increased significantly in the last decade. Hence, in line with the findings of for example Ben-David et al. (2018), the accumulated impact of ETFs on volatility should be higher. At the same time, other literature indicates that an expansion of the ETF market could have the opposite effect. As illustrated by Malamud (2015), increased ETF presence can theoretically mitigate, and potentially even cancel out, the adverse effect on volatility previously caused by ETFs. The introduction of new ETFs can, if they are properly designed, create a demand substitution effect. As new ETFs are introduced, demand shocks continue to influence the dynamics of the security prices, in line with

Ben-David's (2018) findings. However, the nature of the trading of ETFs also changes, which changes how demand shocks are distributed across different markets. Hence, the introduction of new ETFs may offset the negative effects of existing ETFs through a demand and volatility substitution effect and render reduced volatility and commonality of the securities. Analyzing a hitherto unexamined time period, under which the number and aggregate AUM of ETFs have significantly increased, may render different results with important implications for the past, present and future research on the subject. New ETFs are flowing in on the market at a high pace. In 2020 alone, over 300 new ETFs were opened and the net number of ETFs on the U.S market increased by over 150 per annum between 2014 and 2020 (ICI, 2021).

Previous literature on the U.S. market has predominantly found positive correlations between ETF ownership and volatility. However, to the best of our knowledge, no paper published in any prominent financial journal has analyzed the relationship between ETF ownership and volatility while distinguishing between the ETF categories. We believe there could be significant differences in the volatility contribution depending on the ETF type. To exemplify, a broad index-tracking ETF and a technology-sector ETF should attract different types of investors with differing levels of sophistication, speculation, and investment horizons. This in turn affects the dynamics of the ETF itself. For instance, a growth fund tends to have a higher turnover than a value fund. A higher turnover puts more pressure on the APs and primary market, which could impact the magnitude of ETFs' effect on volatility of the underlying. Furthermore, some literature suggest that increased index investing could decrease price informativeness leading to less unification in the investor base, potentially resulting in additional volatility in the underlying asset. This could possibly be manifested through different magnitudes of volatility contributions depending on whether the ETF is passive and index-tracking or actively managed. In recent years, an increasing number of actively managed ETFs have entered the market. Furthermore, leveraged ETFs have characteristics not shared by traditional ETFs. Daily re-hedging by leveraged funds could for example amplify existing volatility on the market, as shown by Cheng & Madhavan (2009). Other aspects, such as shorter investor holding periods and higher premiums and discounts (Charupat & Miu, 2011), could cause leveraged funds to affect the attributes of the underlying asset to a different degree. By nature, leveraged ETFs possess a more aggressive investor base, as its very purpose is to generate a multiple of the underlying returns.

As such, recent research calls for a more granular analysis of ETFs that also accounts for recent market developments. To the best of our knowledge, our extension of previous literature is in this regard novel.

4. Data

4.1 Data Collection and Description

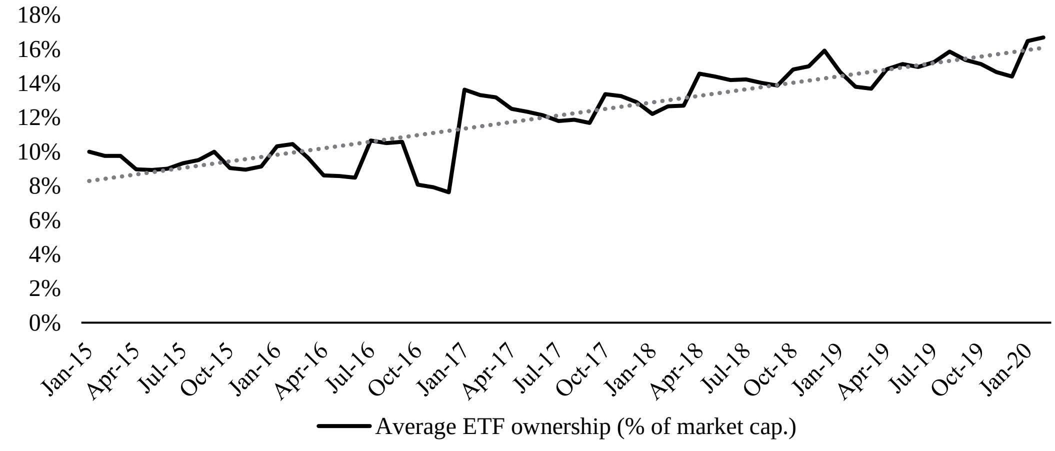
Firstly, we define and extract a specific set of ETFs that track or have exposure to the S&P 500. This is done through S&P Capital IQ and yields an initial data set consisting of 561 unique ETFs. We then perform additional screening by limiting our sample to ETFs that are listed on US exchanges and omit ETFs with market capitalizations of below USD 50M. This is done in order to mitigate the impact of illiquidity and potential price discrepancies caused by infrequent trading, and follows the example of Brown et al (2021). Finally, we end up with a set of 282 U.S. traded ETFs exposed to the S&P 500.

Utilizing CRSP through WRDS, we then find the ETFs specific portfolio numbers. Using the portfolio numbers, we can then search for quarterly data on portfolio compositions, which we do for the time period 01/01/2015 -31/12/2021. To determine the accumulated ETF ownership of the index, we sum the aggregate market value of the ETF set's holdings in each constituent security. We then divide this with the actual market value of the security in the corresponding time period, which yields a growing trend of ownership. ETF ownership is measured in monthly intervals.

Figure 2

ETF Ownership Development - S&P 500

Mean ownership of the S&P 500 stocks, measured on a monthly basis between January 2015 and January 2020



In order to examine the volatility impact of ETF ownership, we then gather high frequency stock-level data on the constituent companies of the S&P 500, as of the 27th of February 2022, again through S&P Capital IQ. Using this data, we compute skewness, logged market capitalization, inverse share price, Amihud ratio, price-to-book ratio, and past-12-month return (PTM) for all constituent companies. These metrics will serve as control variables in following regressions. Every control variable except PTM is lagged one month to limit omitted variable bias and provide a more robust estimate. Daily stock volatility is computed as the standard deviation of daily returns over a month, at the monthly frequency. This volatility computation is in line with previous literature (Ben-David (2018)).

Table 1
Summary statistics
The table presents summary statistics for the variables used in the study. The sample covers the period between January 2015 to January 2020.

	N	Mean	Std Dev	Min	25%	50%	75%	Max
Volatility (%)	26,852	1.484	0.720	0.500	0.980	1.320	1.800	4.430
Amihud ratio (scaled 10^6)	26,852	7.382	36.371	-111.977	-6.223	3.439	18.339	156.455
ETF ownership	26,852	0.123	0.059	0.000	0.093	0.134	0.165	0.233
Inverse price	26,852	0.018	0.015	0.001	0.009	0.014	0.022	0.083
Log mkt. capitalization ($bn)	26,852	4.366	0.441	3.474	4.048	4.300	4.622	5.608
Price-to-book ratio	26,852	6.096	8.563	0.756	2.104	3.496	6.330	61.033
Skewness	26,852	-0.098	0.981	-2.955	-0.632	-0.095	0.431	2.835
Past 12-month returns	26,852	0.197	0.709	-0.792	-0.069	0.098	0.276	5.498

The fact that ETF data is only accessible quarterly increases the risk of misleading correlation between volatility and ETF ownership. By including and lagging the control variables of Table 1, we enhance the validity of our analysis in the following ways: The logged market capitalization mitigates the risk of finding a misleading correlation as a consequence of the mechanics of equal weighted ETFs, as the underlying securities' market capitalization and the market capitalization of the stocks in the equal-weighted ETF do not develop proportionately. This follows the example of Ben-David et al. (2018). The endogeneity issues related to firm size and liquidity are addressed through our inclusion of the Amihud ratio and the inverse share price. The Amihud ratio is calculated by dividing return by the dollar volume. As volatility can be affected by return indicators, we include both Price-To-Book and PTM. To deal with any potential autocorrelation, the dependent variable is lagged three times. Finally, we add fixed effects that control for company specific and time-dependent omitted variables. We perform three separate regressions - one without fixed effects, one with a monthly-fixed effect and one including both monthly and firm fixed effects. Month fixed effects controls for period-related variability whereas firm fixed effects capture cross sectional differences between the stocks.

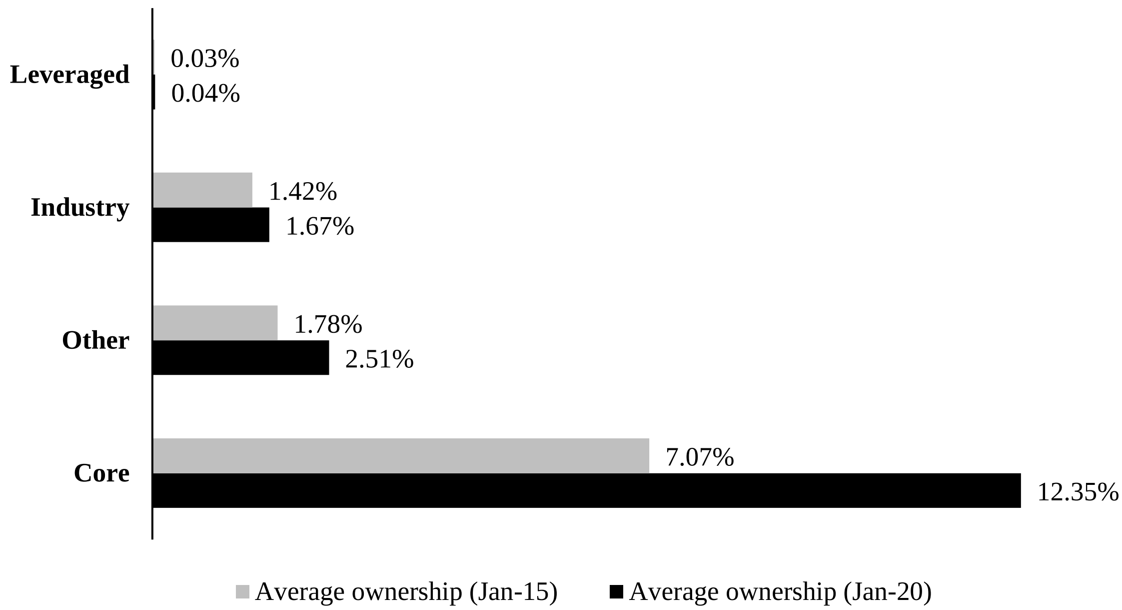
After regressing with our entire defined set of ETFs, we continue with dividing the funds into distinct categories, and study each group's potential effect separately. To accurately classify the ETFs, we make use of the Lipper classification - a system often used to categorize different types of funds. Refinitiv Lipper is provided by Thomson-Reuters and the data is accessible through CRSPs Mutual Fund database. The Lipper system classifies our ETFs into a total of 57 categories and these classifications serve as a base for us to categorize the funds into 4 groups - Core, Industry, Leveraged and Other.

Table 2
Summary statistics – ETF types
The table presents summary statistics for the different ETF classification groups. Aggregate assets under management (AUM) represents the mean total quarterly AUM observation period for the respective categories, measured in millions of dollars. AUM share of ETF market represents the market share attributable to each respective category. Mean fund AUM is the average ETF size, and is observed on a monthly basis. The observation period covers January 2015 - January 2020.

	All	Core	Industry	Leveraged	Other
Number of Funds	282	87	50	42	103
Aggregate AUM ($m)	2,645,573	1,951,274	310,533	7,494	376,272
AUM share of ETF market	100.0%	73.8%	11.7%	0.3%	14.2%
Mean fund AUM ($m)	9,381	22,428	6,211	178	3,653

Among our final set of 282 ETFs, 87 funds are placed in Core, 50 in Industry, 42 in Leveraged, and 103 in Other. Core constitutes the backbone of the market with three-quarters of the total AUM. It also possesses the largest funds, shown by a significantly higher AUM per fund than the other three categories. Industry, Leveraged and Other all possess a higher number of funds in relation to their share of the total AUM. As illustrated in figure 3, Core ETFs grew the most between Jan-15 and Jan-20, increasing their average ownership share in the underlying stocks by 75%, which equals an increase of 5.3 percentage points. Alternative ETFs have also risen to become a substantial part of underlying stock holdings: The Other category, including e. g. high-dividend and growth ETFs, have grown their average ownership share in the underlying by 41%, representing an increase of 0.73 percentage points. Leveraged ETFs grew their average stake by 27%, although only averaging 0.04% ownership in the underlying stocks as of Jan-20. Industry ETFs grew by 17%, reaching 1.67% average ownership.

Figure 3
Average ownership by ETF type
Average ownership share of the S&P 500 stocks held by the distinct ETF categories, January 2015 and January 2020



A full breakdown of the classifications of the different Lipper subcategories can be found in Appendix 1.

4.2 Data Processing and Cleaning

The collected dataset initially stretched until 31/12/2021, but was cut at 31/01/2020. The reason behind this is the period of significantly increased volatility amidst the Covid-19 pandemic. The data following the market crash was more specifically excluded for two reasons. Firstly, inclusion of the final 23 months would risk rendering skewed ETF ownership for securities that were highly impacted by Covid-19, as ETF ownership data is only obtainable quarterly whilst our other data is measured monthly. Secondly, examining a relatively stable time period reduces the risk and magnitude of exogenous factors negatively affecting the validity of our output.

Inverse ETFs were decided to be excluded from the dataset due to the nature of our main testable hypothesis - as inverse ETFs take negative ownership positions in the underlying, that complicates and risks negatively impacting our measurements of ownership. The market size of inverse ETFs constitutes a trivial share of the total market for ETFs - according to ETF Database, we find that there are 85 inverse ETFs with a market capitalization of $16bn on the U.S. market.

The price-to-book values of SBA Communications Corp were for a period of time negative, and were hence cleaned. As IHS Markit Ltd. and Constellation Energy Corporation were recently listed, no observations were available for our research period. Consequently, these two S&P 500 constituents were removed from the sample. To limit the risk of spurious effects caused by extreme values, we winsorize our data at the 1% and 99% levels.

4.3 Limitations

ETF ownership is only attainable quarterly, which is suboptimal for achieving the most accurate results. Data on the monthly ownership could yield different results. As opposed to Ben-David et al. (2018), we do not include the bid-ask spread, the gross profitability, nor other funds' ownership (index funds, hedge funds and active funds) as control variables, due to data access issues. The lack of these control variables could have a negative impact on our regressions.

5. Results

5.1 Complete ETF-set

Table 3
OLS regression: ETF ownership on stock volatility

*The following table provides estimates from the OLS regression of volatility on ETF ownership and control variables. The sample is monthly. Volatility is computed as the log daily returns within a month and has been lagged three times. The control variables include Amihud (2002) illiquidity measure which is scaled 10^6, inverse share price, the logged market capitalization, the price-to-book ratio, skewness and past 12-month return. T-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The observations cover the time period between April 2015 - January 2020. (January - March 2015 are not included to the absence of lagged dependent variables).*

OLS Regressions, Full Sample			
Dependent Variable:	Volatility		
	(1)	(2)	(3)
ETF ownership	-0.003***	-0.004***	0.001
	(-4.218)	(-6.989)	(0.846)
Amihud (t-1)	0.000	0.000	0.000
	(0.529)	(-1.026)	(-0.349)
Price-To-Book (t-1)	0.000***	0.000	0.000
	(3.337)	(0.838)	(0.495)
Inverse price (t-1)	-0.152***	-0.098***	-0.104***
	(-4.408)	(-3.141)	(-3.408)
log (Market cap (t-1))	0.050***	0.026***	-0.024***
	(24.020)	(13.467)	(11.793)
Skewness (t-1)	0.000***	-0.000	0.000
	(3.997)	(0.769)	(-1.583)
Past 12-month return	0.000	0.000***	0.000
	(0.592)	(2.678)	(-0.137)
Volatility (t-1)	0.246***	0.176***	0.038***
	(43.101)	(30.584)	(6.324)
Volatility (t-2)	0.172***	0.186***	0.052***
	(29.873)	(32.767)	(8.710)
Volatility (t-3)	0.292***	0.328***	0.194***
	(51.733)	(57.708)	(32.657)
Stock fixed effects	No	No	Yes
Month fixed effects	No	Yes	Yes
No. Observations	26,852	26,852	26,852
Adjusted R^2	0.873	0.465	0.513
Note:	*p<0.1; **p<0.05; ***p<0.01		

The results of the first regression, performed on the complete set of ETFs and including several lagged controls, are reported in Table 3. Our results differ from previous literature and are not in line with what we hypothesized, as we find that ETF ownership is negatively correlated with the dependent variable, with a coefficient on ETF ownership of -0.003. This translates to one standard deviation unit increase in ETF ownership leading to a decrease in volatility by 0.3% of a standard deviation. The magnitude of the relationship is hence relatively faint. The adjusted R-squared in the regression has a value of 0.873, meaning almost 90% of the variance of the dependent variable is explained by the variance of our independent variables. The results are highly statistically significant (1% level), and contrast the findings of Ben-David et al. (2018) that ETF ownership has a statistically significant positive relationship with volatility of daily returns on S&P 500 stocks.

To further strengthen the validity of these findings, we want to control for both time and company fixed effects, firstly regressing with only a time fixed effect. This yields an even stronger negative correlation between ETF ownership and volatility, with an ETF ownership coefficient of -0.004, representing a weak but significant negative relationship. The adjusted R-squared is now lower with a value of 0.465, suggesting not as much of the variation of the dependent variable can be explained by the model. Also including firm fixed effects, we find a slight positive correlation between volatility and ETF ownership with a coefficient on ETF ownership of 0.001. Additionally, the adjusted R-squared increases to 0.523. However, the ETF ownership coefficient is insignificant, with a p-value of 0.397. The results motivate us to investigate the discrepancy between our results and those of Ben-David et al (2018).

5.2 Effect by ETF Category

Table 4

OLS regression: ETF ownership by fund type

*The following table provides estimates from the OLS regression of volatility on ETF ownership and control variables. The sample is monthly. Volatility is computed as the log daily returns within a month and has been lagged three times. The control variables include Amihud (2002) illiquidity measure which is scaled 10^6, inverse share price, the logged market capitalization, the price-to-book ratio, skewness and past 12-month return. T-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The observations cover the time period between April 2015 - January 2020. (January - March 2015 are not included to the absence of lagged dependent variables).*

OLS Regressions by ETF type

Dependent Variable:	Volatility			
	Core	Industry	Leveraged	Other
ETF ownership	-0.004***	-0.017***	0.352*	0.003
	(-4.593)	(-5.883)	(1.677)	(1.153)
Amihud (t-1)	0.000	0.000	0.000	0.000
	(0.456)	(0.303)	(0.715)	(0.516)
Price-To-Book (t-1)	0.000***	0.000***	0.000***	0.000***
	(3.331)	(3.262)	(3.483)	(3.431)
Inverse price (t-1)	-0.153***	-0.153***	-0.155***	-0.154***
	(-4.422)	(-4.410)	(-4.492)	(-4.452)
log (Market cap (t-1))	0.050***	0.050***	0.050***	0.050***
	(24.021)	(23.948)	(23.678)	(23.769)
Skewness (t-1)	0.000***	0.000***	0.000***	0.000***
	(4.016)	(4.043)	(4.232)	(4.250)
Past 12-month return	0.000	0.000	0.000	0.000
	(0.564)	(0.776)	(1.015)	(1.071)
Volatility (t-1)	0.246***	0.245***	0.247***	0.247***
	(43.101)	(42.955)	(43.175)	(43.179)
Volatility (t-2)	0.172***	0.171***	0.172***	0.172***
	(29.873)	(29.570)	(29.865)	(29.812)
Volatility (t-3)	0.292***	0.291***	0.293***	0.293***
	(51.733)	(51.457)	(51.794)	(51.772)
Stock fixed effects	No	No	No	No
Month fixed effects	No	No	No	No
No. Observations	26,852	26,852	26,852	26,852
Adjusted R^2	0.873	0.873	0.873	0.873
Note:	*p<0.1; **p<0.05; ***p<0.01			

Our regressions for the distinct ETF categories, reported in Table 4, suggest that the effect of fund ownership on volatility differs depending on the ETF type. All regressions are performed in accordance with the first regression on the entire ETF set, only changing the ETF ownership variable to exclusively include the ownership specific to the category that is being examined. Firstly, we find that Core ETF ownership negatively correlates with volatility with a coefficient of -0.004, at a 1% significance level. Industry ETF ownership is found to have an even stronger negative relationship, with a coefficient of -0.017, also at a 1% significance level. The results for the remaining two categories, Leveraged ETFs and Other ETFs, are more in line with our main hypothesis, namely that ETF ownership is positively correlated with volatility. The Leveraged category shows the strongest positive relationship with a coefficient of 0.352, with significance at the 10% level. Other ETFs had a less positive coefficient of 0.003, but not with statistical significance.

As reported in Table 5, the inclusion of stock and month fixed effects yield insignificant ETF ownership coefficients for Core, Industry and Leveraged. The only regression yielding a significant result is Other, showing a positive relationship between ETF ownership and the dependent variable that is slightly stronger than in the previous regression, with significance at the 5% level.

Table 5
OLS regressions by ETF type including fixed effects
*The following table provides estimates from the OLS regression of volatility on ETF ownership and control variables. The sample is monthly. Volatility is computed as the log daily returns within a month and has been lagged three times. The control variables include Amihud (2002) illiquidity measure which is scaled 10^6, inverse share price, the logged market capitalization, the price-to-book ratio, skewness and past 12-month return. T-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The observations cover the time period between April 2015 - January 2020. (January - March 2015 are not included to the absence of lagged dependent variables).*

OLS Regressions by ETF type

Dependent Variable:	Volatility			
	Core	Industry	Leveraged	Other
ETF ownership	-0.001	0.009	0.300	0.017**
	(-0.765)	(1.385)	(0.892)	(2.378)
Amihud (t-1)	0.000	0.000	0.000	0.000
	(-0.386)	(-0.333)	(-0.364)	(-0.338)
Price-To-Book (t-1)	0.000	0.000	0.000	0.000
	(0.484)	(0.514)	(0.495)	(0.480)
Inverse price (t-1)	-0.104***	-0.103***	-0.104***	-0.103***
	(-3.399)	(-3.381)	(-3.400)	(-3.370)
log (Market cap (t-1))	0.023***	0.023***	0.023***	0.023***
	(11.998)	(11.853)	(11.873)	(11.779)
Skewness (t-1)	0.000***	0.000	0.000	0.000
	(-1.603)	(-1.569)	(-1.583)	(-1.589)
Past 12-month return	0.000	0.000	0.000	0.000
	(-0.134)	(-0.161)	(-0.154)	(-0.139)
Volatility (t-1)	0.038***	0.038***	0.038***	0.038***
	(6.356)	(6.311)	(6.327)	(6.276)
Volatility (t-2)	0.052***	0.052***	0.052***	0.051***
	(8.737)	(8.698)	(8.711)	(8.667)
Volatility (t-3)	0.194***	0.194***	0.194***	0.194***
	(32.658)	(32.659)	(32.646)	(32.632)
Stock fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
No. Observations	26,852	26,852	26,852	26,852
Adjusted R^2	0.513	0.513	0.513	0.513

Note: *p<0.1; **p<0.05; ***p<0.01

6. Analysis

Our first regression implies that there is a negative correlation between ETF ownership and volatility at the 1% significance level, which also holds when time fixed effects are included. However, when also including company fixed effects, the results become insignificant. This implies that there is no correlation between ETF ownership and volatility of the underlying assets, and that the previously established positive correlation, as found by e. g. Ben-David et al. (2018), is not present in the time period between January 2015 and January 2020. This analysis is primarily aimed at examining possible reasons behind the rejection of our main testable hypothesis. As the precedent paper of Ben-David et al. made conclusions aligned with our main hypothesis, we start by comparing summary statistics.

6.1 Comparison with Ben David et. al (2018)

Setting our summary statistics side by side with Ben- David et. al (2018), the most apparent difference is the change in mean ETF ownership. We observe a mean of 0.123, corresponding to ~12% average ownership, whilst the precedent paper shows an average ownership of ~3%. This is in line with our expectations, as ETFs have grown in the ten-folds in value and quantity since January 2000, which is the date of the first observation in Ben- David et al. Also notable is that the mean volatility has decreased approximately 25% – Ben-David et al. observed a mean of ~2%, while our data had a mean of ~1.5%. An explanatory factor could be that our analysis period does not include any major market crashes. The mean of the inverse share price is lower in our dataset, which is reasonable considering that the average firm size has grown. Ben-David et al. use the book-to-market metric instead of price-to-book. Their mean converted to price-to-book is much lower than ours, which illustrates how companies in the S&P 500 are increasingly being valued higher than their book assets. The PTM return statistic tells a story of higher growth and a wider distribution of returns between companies in our sample period, as we observe a greater standard deviation.

In sum, the comparison of summary statistics highlights some major differences, and displays a changed market landscape.

6.2 Shock Propagation, Volatility Substitution and Liquidity Buffer

The number of ETFs in the U.S has increased over 38% between 2015, which is the end of the data period in the paper of Ben-David et al. (2018), and 2020. While ETFs may serve as a catalyst for short-horizon liquidity trading, and propagation of liquidity shocks through the arbitrage channels can increase the volatility of the underlying equities, the increased number of ETFs may counteract this to the degree that the effect becomes net zero. In accordance with Malamud (2015) "A Dynamic Equilibrium Model of ETFs", substitution of demand in line with the inflow of new funds may have significantly decreased the pressure on the arbitrage channels. Allowing for demand shocks to continue to influence the dynamics of the security prices, the nature of the trading of ETF shares has changed, which in turn also changes how demand shocks are distributed across different markets. This resonates well with the new ETF landscape – an increased number of funds with a wider coverage may have offset previously established adverse effects through a volatility substitution effect, and rendered reduced volatility. This explanation, anchored in Malamud's theory, is to a certain extent related to the argument put forward by Grossman (1988), that futures add a new layer of market making power acting as a liquidity buffer, which in turn reduces spot market volatility. It is possible to extend this phenomenon to ETFs – liquidity shocks on the underlying securities could be mitigated and absorbed by the additional layer of liquidity that ETFs provide – resulting in lower volatility in the underlying stock. While this appears counterfactual to literature such as Ben-David et al. (2018), illustrating how price pressure from ETF flows and arbitrage activity increases volatility, these effects could occur simultaneously, which would affect volatility in opposite directions.

Assuming the arbitrage mechanism in ETFs still generates increased volatility in the underlying equities, and considering the results of our regressions indicate that the relationship between volatility and ETF ownership is either slightly negative or non-existent, our research would, with regard to previous literature, suggest we are in a form of equilibrium. Though we are unable to separate and quantify the effects of, for example, potentially increased volatility generated by the primary market and decreased volatility through ETFs providing a liquidity buffer, the ETF ownership effect on volatility is found to be close to zero.

6.3 Market Composition

Our output indicates that ETF ownership's effect on the volatility of the underlying assets differs in both effects, as we found both positive and negative relationships, and magnitude of effect depending on the category of the ETF. Core constitutes a vast majority of the market, and their effect is hence most relevant for the accumulated effect. As the other coefficients significantly differed from Core, it is possible that the composition of ETFs may have had an incremental effect on the relationship we found. Although strong effects from the other categories would leave a dent, their magnitude would be small considering the weight distribution. The coefficients would therefore have to be immense to make a considerable difference, which ours were not. Hence, we can ascertain that the differences between our findings and those of Ben-David et al. (2018) are not mainly attributable to a changed market composition of ETFs.

6.4 Reverse Causality and Pressure on Arbitrage Channels

The results indicate support for our second hypothesis – that ETF ownership affects volatility to different degrees, depending on the ETF category. Both Core and Industry had negative ETF ownership coefficients, whilst Leveraged and Other had positive coefficients. However, the statistical significance varied, and including time and firm fixed effects, only the regression of Other produced significant findings at the 5% level. Hence, we can not draw any causal inference between ETF ownership and volatility for all ETF types with high statistical significance. This should be taken into consideration in the following part of the analysis.

A reason for the differences in the coefficients for the ETF types could be a reverse causality relationship between the ETF and the stock. For example, a growth-focused fund, that would be included in the Other category, invests in stocks that by themselves are more volatile. This could provide explanatory value for why Other has a positive ETF ownership coefficient. With similar reasoning, companies that belong to many indices will have higher ETF ownership. As these large and well-established firms tend to be less volatile, this would create a negative bias, which would explain the negative coefficient for Core. Hence, there is a possibility that the volatility of the stock affects ETF ownership – different stocks attract different ETFs with different investment styles. This is in line with the fact that our established negative correlation becomes insignificant when controlling for firm fixed effects.

ETFs attract different types of investors with differing levels of sophistication, speculation and investment horizons depending on their investment style. Naturally, this will affect the dynamics of the ETF itself. As the Other category mainly consists of growth funds, the turnover for this category should be higher than for Core, which primarily comprises index tracking funds. As such, they direct different amounts of pressure on the arbitrage channels through which shocks, in accordance with Ben-David, may propagate. By definition, Other and Leveraged should exert more pressure, being the preferred habitat for high turnover investors. This would help explain the positive coefficients of these categories.

7. Discussion and Conclusion

ETFs have undoubtedly provided considerable advantages for private investors and institutions alike, and risen as one of the foremost investment vehicles on the market. However, strong indications of inadvertent effects on the underlying assets from prominent literature, and significant growth of the ETF market in the last five years - a period that has not been thoroughly researched - necessitates an analysis of the relationship between ETF ownership and volatility of the underlying assets. Examining data on ETFs connected to the S&P 500, and the constituents of the index, through regression models, we find no positive correlation between increased ETF ownership and volatility, which contrasts the findings of precedent research. Additionally, we provide novel insight through studying the effects of different ETF categories separately. Our findings suggest that effects and magnitude differ between the different ETF types, with varying significance.

Our findings deviate from previous literature such as Ben-David et. al (2018), who showed that ETFs may increase volatility of the underlying equities though enabling propagation of liquidity shocks. Though recognizing that these mechanics may still be at play, we hypothesize that counteracting factors could help explain our results. A volatility substitution effect stemming from the high inflow of ETFs, and that ETFs may simultaneously function as a liquidity buffer for the underlying stocks, could provide explanatory value. Moreover, we highlight that the vast majority of ETFs are index tracking, which potentially could be indicative of a reverse causality effect due to the assets held.

To improve statistical significance, future papers should strive to expand the sample. For example, both the high frequency stock-level data and the number of ETFs could be extended through also including the Russell 3000 index. Moreover, our data does not allow us to identify and examine the precise mechanisms through which volatility of the securities is affected by an increase in ETF ownership. The ETF ownership variable is instead assumed to function as a proxy for all effects caused by both primary and secondary market activity (AP-, arbitrage- and liquidity trading). The factor may also encapsulate other effects on volatility, such as spillover effects from different markets, meaning one should be cautious with assuming any causal inference on the basis of our results. An extension aimed at isolating the separate effects would possibly help explain the contrast of our findings to that of precedent papers. Although we assert various methods to improve the robustness of our results, the validity of the data analysis could be further improved. As reverse causality could explain the different coefficients of ETF ownership in the four ETF categories, a suitable extension of our analysis would be to examine the direction of causality in the form of a quasi-natural experiment.

Finally, Ben David et al. finds that the positive coefficient of ETF ownership is the highest during a period of crisis (2007-2008). An analysis of the Corona crisis would be an interesting extension and could provide additional insight on whether market liquidity influences the effect that ETFs have on the underlying securities due to ETF arbitrage having a larger impact on stock prices during crises.

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Appendix

Appendix 1

ETF classifications

Classification names are extracted using Refinitiv Lipper provided by Thomson-Reuters and the data is accessible through CRSPs Mutual Fund database. The Lipper system classifies our ETFs into a total of 57 categories which we then proceed to classify into the most suitable category.

ETF types			
Core	Industry	Leveraged	Other
Global Large-Cap Core	Basic Materials Funds	Alternative Long/Short Eqty Fds	Absolute Return Funds
International Large-Cap Core	Commodities Energy Funds	Alternative Long/Short Equity Funds	Alternative Act Extension Fds
International Small/Mid-Cap Core	Commodities General Funds	Dedicated Short Bias Funds	Alternative Managed Futures Funds
Large-Cap Core Funds	Consumer Goods Funds	Diversified Leverage Funds	Equity Income Funds
Mid-Cap Core Funds	Consumer Services Funds	Equity Leverage Funds	Global Equity Income Funds
Multi-Cap Core Funds	Emerging Markets Funds	Long/Short Equity Funds	Global Large-Cap Growth
S&P 500 Index Funds	Energy MLP Funds	Options Arbitrage/Opt Strat Fds	Global Large-Cap Value
S&P 500 Index Objective Funds	Financial Services Funds		Global Real Estate Funds
Small-Cap Core Funds	Flexible Portfolio Funds		Global Small-/Mid-Cap Funds
	Global Science/Technology Fds		Large-Cap Growth Funds
	Health/Biotechnology Funds		Large-Cap Value Funds
	Industrials Funds		Loan Participation Funds
	Natural Resources Funds		Mid-Cap Growth Funds
	Real Estate Funds		Mid-Cap Value Funds
	Science & Technology Funds		Mixed-Asset Target Alloc Consv
	Telecommunication Funds		Mixed-Asset Target Alloc Growth
	Utility Funds		Multi-Cap Growth Funds
			Multi-Cap Value Funds
			Multi-Sector Income Funds
			Short Investment Grade Debt Funds
			Short-Intmdt Investment Grade Debt
			Small-Cap Growth Funds
			Small-Cap Value Funds
			Specialty/Miscellaneous Funds

Appendix 2

Complete list of ETFs

The following table constities our complete set of 282 ETFs exposed to the S&P 500, which have been aggregated in the thesis in order to calculate ETF ownership.

List of ETFs	
Absolute Shares Trust: WBI Large Cap Tactical Select Shares	First Trust Exchange-Traded Fund VIII: First Trust Active Factor Large Cap ETF
Absolute Shares Trust: WBI Large Cap Tactical Value Shares	First Trust Exchange-Traded Fund VIII: First Trust Active Factor Small Cap ETF
Absolute Shares Trust: WBI Large Cap Tactical Yield Shares	First Trust Exchange-Traded Fund VIII: First Trust CEF Income Opportunity ETF
Absolute Shares Trust: WBI Power Factor High Dividend ETF	First Trust Exchange-Traded Fund VIII: FT Cboe Vest US Equity Buffer ETF - November
AdvisorShares Trust: AdvisorShares Dorsey Wright Micro-Cap ETF	First Trust Exchange-Traded Fund VIII: FT Cboe Vest US Equity Deep Buffer ETF - August
AdvisorShares Trust: AdvisorShares Dorsey Wright Short ETF	First Trust Exchange-Traded Fund VIII: FT Cboe Vest US Equity Deep Buffer ETF - November
AdvisorShares Trust: AdvisorShares Focused Equity ETF	FlexShares Trust: FlexShares STOXX US ESG Impact Index Fund
AdvisorShares Trust: AdvisorShares Pacific Asset Enhanced Floating Rate ETF	Global X Funds: Global X Russell 2000 Covered Call ETF
AdvisorShares Trust: AdvisorShares Pure Cannabis ETF	Global X Funds: Global X S&P 500 Catholic Values ETF
AdvisorShares Trust: AdvisorShares Vice ETF	Global X Funds: Global X S&P 500 Quality Dividend ETF
AdvisorShares Trust: Ranger Equity ETF	Innovator ETFs Trust: Innovator Russell 2000 Power Buffer ETF - October
AdvisorShares Trust: TrimTabs Float Shrink ETF	Innovator ETFs Trust: Innovator S&P 500 Buffer ETF - April
ALPS ETF Trust: Alps Equal Sector Weight ETF	Innovator ETFs Trust: Innovator S&P 500 Buffer ETF - August
ALPS ETF Trust: RiverFront Dynamic US Dividend Advantage ETF	Innovator ETFs Trust: Innovator S&P 500 Buffer ETF - December
Amplify ETF Trust: Amplify Transformational Data Sharing ETF	Innovator ETFs Trust: Innovator S&P 500 Buffer ETF - January
Amplify ETF Trust: Amplify YieldShares CWP Dividend & Option Income ETF	Innovator ETFs Trust: Innovator S&P 500 Buffer ETF - July
ARK ETF Trust: ARK Fintech Innovation ETF	Innovator ETFs Trust: Innovator S&P 500 Buffer ETF - June
ARK ETF Trust: ARK Genomic Revolution Multi-Sector ETF	Innovator ETFs Trust: Innovator S&P 500 Buffer ETF - November
ARK ETF Trust: ARK Innovation ETF	Innovator ETFs Trust: Innovator S&P 500 Buffer ETF - October
Arrow Investments Trust: Arrow DWA Tactical ETF	Innovator ETFs Trust: Innovator S&P 500 Buffer ETF - September
Cambria ETF Trust: Cambria Cannabis ETF	Innovator ETFs Trust: Innovator S&P 500 Power Buffer ETF - April
Cambria ETF Trust: Cambria Core Equity ETF	Innovator ETFs Trust: Innovator S&P 500 Power Buffer ETF - August
Cambria ETF Trust: Cambria Shareholder Yield ETF	Innovator ETFs Trust: Innovator S&P 500 Power Buffer ETF - December
Cambria ETF Trust: Cambria Value and Momentum ETF	Innovator ETFs Trust: Innovator S&P 500 Power Buffer ETF - January
Cohen & Steers Global Realty Fund, Inc; Class A Shares	Innovator ETFs Trust: Innovator S&P 500 Power Buffer ETF - July
Cohen & Steers Global Realty Fund, Inc; Class B Shares	Innovator ETFs Trust: Innovator S&P 500 Power Buffer ETF - June
Cohen & Steers Global Realty Fund, Inc; Class C Shares	Innovator ETFs Trust: Innovator S&P 500 Power Buffer ETF - November
Cohen & Steers Global Realty Fund, Inc; Class I Shares	Innovator ETFs Trust: Innovator S&P 500 Power Buffer ETF - October
Cohen & Steers Global Realty Shares, Inc; Class R Shares	Innovator ETFs Trust: Innovator S&P 500 Power Buffer ETF - September
Cohen & Steers Global Realty Shares, Inc; Class Z Shares	Innovator ETFs Trust: Innovator S&P 500 Ultra Buffer ETF - April
Davis Fundamental ETF Trust: Davis Select Financial ETF	Innovator ETFs Trust: Innovator S&P 500 Ultra Buffer ETF - August
Davis Fundamental ETF Trust: Davis Select US Equity ETF	Innovator ETFs Trust: Innovator S&P 500 Ultra Buffer ETF - December
DBX ETF Trust: Deutsche X-trackers Russell 1000 Comprehensive Factor ETF	Innovator ETFs Trust: Innovator S&P 500 Ultra Buffer ETF - January
DBX ETF Trust: Xtrackers Russell 1000 US QARP ETF	Innovator ETFs Trust: Innovator S&P 500 Ultra Buffer ETF - July
DBX ETF Trust: Xtrackers S&P 500 ESG ETF	Innovator ETFs Trust: Innovator S&P 500 Ultra Buffer ETF - June
DFA Investment Dimensions Group Inc: Tax-Managed US Small Cap Portfolio	Innovator ETFs Trust: Innovator S&P 500 Ultra Buffer ETF - November
Direxion Shares ETF Trust: Direxion Auspice Broad Commodity Strategy ETF	Innovator ETFs Trust: Innovator S&P 500 Ultra Buffer ETF - October
Direxion Shares ETF Trust: Direxion Daily Financial Bull 3X Shares	Innovator ETFs Trust: Innovator S&P 500 Ultra Buffer ETF - September
Direxion Shares ETF Trust: Direxion Daily S&P 500 Bear 1X Shares	Invesco Exchange-Traded Fund Trust: Invesco S&P 500 Equal Weight Communication Services ETF
Direxion Shares ETF Trust: Direxion Daily S&P 500 Bull 2X Shares	Investment Managers Series Trust II: Cannabis Growth Fund; Institutional Class Shares
Direxion Shares ETF Trust: Direxion Daily S&P 500 High Beta Bear 3X Shares	Investment Managers Series Trust II: Cannabis Growth Fund; Investor Class Shares
Direxion Shares ETF Trust: Direxion Daily S&P 500 High Beta Bull 3X Shares	iShares Trust: iShares Dow Jones US Basic Materials Sector Index Fund
Direxion Shares ETF Trust: Direxion Russell 1000 Growth Over Value ETF	iShares Trust: iShares Dow Jones US Consumer Goods Sector Index Fund
Direxion Shares ETF Trust: Direxion Russell 1000 Value Over Growth ETF	iShares Trust: iShares Dow Jones US Consumer Services Sector Index Fund
EntrepreneurShares Series Trust: ERShares Entrepreneur 30 ETF	iShares Trust: iShares Dow Jones US Energy Sector Index Fund
ETF Managers Trust: AI Powered Equity ETF	iShares Trust: iShares Dow Jones US Financial Sector Index Fund
ETF Series Solutions: AAM S&P 500 High Dividend Value ETF	iShares Trust: iShares Dow Jones US Healthcare Sector Index Fund
ETF Series Solutions: Acquirers Fund	iShares Trust: iShares Dow Jones US Industrial Sector Index Fund
ETF Series Solutions: AlphaMark Actively Managed Small Cap ETF	iShares Trust: iShares Dow Jones US Technology Sector Index Fund
ETF Series Solutions: Aptus Behavioral Momentum ETF	iShares Trust: iShares Dow Jones US Telecommunications Sector Index Fund
ETF Series Solutions: Aptus Collared Income Opportunity ETF	iShares Trust: iShares Dow Jones US Utilities Sector Index Fund
ETF Series Solutions: Cboe Vest S&P 500 Dividend Aristocrats Target Income ETF	iShares Trust: iShares Russell 1000 Growth Index Fund
ETF Series Solutions: Distillate US Fundamental Stability & Value ETF	iShares Trust: iShares Russell 1000 Index Fund
ETF Series Solutions: Opus Small Cap Value Plus ETF	iShares Trust: iShares Russell 1000 Value Index Fund
ETF Series Solutions: Point Bridge GOP Stock Tracker ETF	iShares Trust: iShares Russell 2000 Growth Index Fund
ETFis Series Trust I: InfraCap MLP ETF	iShares Trust: iShares Russell 2000 Index Fund
ETFis Series Trust I: Reaves Utilities ETF	iShares Trust: iShares Russell 2000 Value Index Fund
Exchange Listed Funds Trust: QRAFT AI-Enhanced US Large Cap ETF	iShares Trust: iShares Russell 2500 ETF
Exchange Listed Funds Trust: QRAFT AI-Enhanced US Large Cap Momentum ETF	iShares Trust: iShares Russell 3000 Growth Index Fund
Exchange Traded Concepts Trust II: Horizons S&P 500 Covered Call ETF	iShares Trust: iShares Russell 3000 Index Fund
Exchange Traded Concepts Trust: Hull Tactical US ETF	iShares Trust: iShares Russell Microcap Index Fund
First Trust Exchange-Traded Fund III: First Trust Horizon Managed Volatility Domestic ETF	iShares Trust: iShares Russell Midcap Growth Index Fund
First Trust Exchange-Traded Fund III: First Trust Long/Short Equity ETF	iShares Trust: iShares Russell Midcap Index Fund
First Trust Exchange-Traded Fund IV: First Trust EIP Carbon Impact ETF	iShares Trust: iShares Russell Midcap Value Index Fund
First Trust Exchange-Traded Fund IV: First Trust North American Energy Infrastructure Fund	iShares Trust: iShares Russell Top 200 Growth Index Fund
First Trust Exchange-Traded Fund IV: First Trust Strategic Income ETF	iShares Trust: iShares Russell Top 200 Index Fund
First Trust Exchange-Traded Fund V: First Trust Morningstar Managed Futures Strategy Fund	iShares Trust: iShares Russell Top 200 Value Index Fund
First Trust Exchange-Traded Fund VII: First Trust Alternative Absolute Return Strategy ETF	iShares Trust: iShares S&P 500 Growth Index Fund
First Trust Exchange-Traded Fund VII: First Trust Global Tactical Commodity Strategy Fund	iShares Trust: iShares S&P 500 Index Fund
First Trust Exchange-Traded Fund VIII: EquityCompass Equity Risk Manager ETF	iShares Trust: iShares S&P 500 Value Index Fund

List of ETFs (cont'd)

KraneShares Trust: KFA Large Cap Quality Divivend IndexETF
KraneShares Trust: KFA Small Cap Quality Divivend IndexETF
Lattice Strategies Trust: Lattice Global Small Cap Strategy ETF
Lattice Strategies Trust: Lattice US Equity Strategy ETF
Legg Mason ETF Investment Trust: ClearBridge Dividend Strategy ESG ETF
Legg Mason ETF Investment Trust: ClearBridge Large Cap Growth ESG ETF
Northern Lights Fund Trust IV: Main Sector Rotation ETF
NuShares ETF Trust: NuShares Enhanced Yield 1-5 Year US Aggregate Bond ETF
Oppenheimer Russell 1000 Dynamic Multifactor ETF
Oppenheimer Russell 1000 Momentum Factor ETF
Oppenheimer Russell 1000 Size Factor ETF
Oppenheimer Russell 1000 Value Factor ETF
Oppenheimer Russell 2000 Dynamic Multifactor ETF
PIMCO Equity Series: PIMCO RAFI Dynamic Multi-Factor US Equity ETF
PowerShares Actively Managed Exchange-Traded Fund Trust: PowerShares Balanced Multi-Asset Allocation Portfolio
PowerShares Actively Managed Exchange-Traded Fund Trust: PowerShares Conservative Multi-Asset Allocation Port
PowerShares Actively Managed Exchange-Traded Fund Trust: PowerShares Growth Multi-Asset Allocation Portfolio
PowerShares Actively Managed Exchange-Traded Fund Trust: PowerShares Moderately Conservative Mlt-Asst Alloc Pf
PowerShares Actively Managed Exchange-Traded Fund Trust: PowerShares S&P 500 Downside Hedged Portfolio
PowerShares Exchange-Traded Fund Trust II: PowerShares Russell 1000 Enhanced Equal Weight Portfolio
PowerShares Exchange-Traded Fund Trust II: PowerShares Russell 1000 Equal Weight Portfolio
PowerShares Exchange-Traded Fund Trust II: PowerShares Russell 1000 Low Beta Equal Weight Portfolio
PowerShares Exchange-Traded Fund Trust II: PowerShares S&P 500 ex-Rate Sensitive Low Volatility Portfolio
PowerShares Exchange-Traded Fund Trust II: Powershares S&P 500 High Beta Portfolio
PowerShares Exchange-Traded Fund Trust II: PowerShares S&P 500 High Dividend Portfolio
PowerShares Exchange-Traded Fund Trust II: Powershares S&P 500 Low Volatility Portfolio
PowerShares Exchange-Traded Fund Trust II: PowerShares S&P 500 Minimum Variance Portfolio
PowerShares Exchange-Traded Fund Trust II: PowerShares S&P 500 Momentum Portfolio
PowerShares Exchange-Traded Fund Trust II: PowerShares S&P 500 Value Portfolio
PowerShares Exchange-Traded Fund Trust II: PowerShares S&P 500 Value with Momentum Portfolio
PowerShares Exchange-Traded Fund Trust: PowerShares Fundamental Pure Large Growth Portfolio
PowerShares Exchange-Traded Fund Trust: PowerShares Fundamental Pure Large Value Portfolio
PowerShares Exchange-Traded Fund Trust: PowerShares S&P 500 BuyWrite Portfolio
PowerShares Exchange-Traded Fund Trust: PowerShares S&P 500 High Quality Portfolio
Principal Exchange-Traded Funds: Principal Contrarian Value Index ETF
ProShares Trust II: Short VIX Short-Term Futures ETF
ProShares Trust II: Ultra VIX Short-Term Futures ETF
ProShares Trust II: VIX Mid-Term Futures ETF
ProShares Trust II: VIX Short-Term Futures ETF
ProShares Trust: ProShares Russell 2000 Dividend Growers ETF
ProShares Trust: ProShares Russell US Dividend Growers ETF
ProShares Trust: ProShares S&P 500 Aristocrats ETF
ProShares Trust: ProShares S&P 500 Bond ETF
ProShares Trust: ProShares S&P 500 Ex-Energy ETF
ProShares Trust: ProShares S&P 500 Ex-Financials ETF
ProShares Trust: ProShares S&P 500 Ex-Health Care ETF
ProShares Trust: ProShares S&P 500 Ex-Technology ETF
ProShares Trust: Ultra Russell2000
ProShares Trust: Ultra S&P 500
ProShares Trust: UltraPro Russell2000
ProShares Trust: UltraPro S&P 500
ProShares Trust: UltraPro Short S&P 500
RBB Fund, Inc: Motley Fool Small-Cap Growth ETF
Renaissance Capital Greenwich Funds: Renaissance IPO ETF
RevenueShares ETF Trust: RevenueShares Large Cap Fund
RydexETF Trust: Guggenheim S&P 500 Equal Weight Real Estate ETF
RydexETF Trust: Rydex Russell Top 50 ETF
RydexETF Trust: Rydex S&P 500 Pure Growth ETF
RydexETF Trust: Rydex S&P 500 Pure Value ETF
RydexETF Trust: Rydex S&P Equal Weight Consumer Discretionary ETF
RydexETF Trust: Rydex S&P Equal Weight Consumer Staples ETF
RydexETF Trust: Rydex S&P Equal Weight Energy ETF
RydexETF Trust: Rydex S&P Equal Weight ETF
RydexETF Trust: Rydex S&P Equal Weight Financial ETF
RydexETF Trust: Rydex S&P Equal Weight Health Care ETF
RydexETF Trust: Rydex S&P Equal Weight Industrial ETF
RydexETF Trust: Rydex S&P Equal Weight Materials ETF
RydexETF Trust: Rydex S&P Equal Weight Technology ETF
RydexETF Trust: Rydex S&P Equal Weight Utilities ETF
Schwab Strategic Trust: Schwab Fundamental Emerging Markets Large Company Index ETF
Schwab Strategic Trust: Schwab Fundamental International Large Company Index ETF
Schwab Strategic Trust: Schwab Fundamental International Small Company IndexETF
Schwab Strategic Trust: Schwab Fundamental US Broad Market Index ETF
Schwab Strategic Trust: Schwab Fundamental US Large Company Index ETF
Schwab Strategic Trust: Schwab Fundamental US Small Company IndexETF
Select Sector SPDR Trust: Consumer Discretionary Select Sector SPDR Fund
Select Sector SPDR Trust: Consumer Staples Select Sector SPDR Fund
Select Sector SPDR Trust: Energy Select Sector SPDR Fund
Select Sector SPDR Trust: Financial Select Sector SPDR Fund
Select Sector SPDR Trust: Industrial Select Sector SPDR Fund
Select Sector SPDR Trust: Materials Select Sector SPDR Fund
Select Sector SPDR Trust: Real Estate Select Sector SPDR Fund
Select Sector SPDR Trust: Technology Select Sector SPDR Fund
Select Sector SPDR Trust: Utilities Select Sector SPDR Fund
SPDR S&P 500 ETF Trust
SPDR Series Trust: SPDR DJ Global Titans ETF
SPDR Series Trust: SPDR Dow Jones Large Cap ETF
SPDR Series Trust: SPDR Dow Jones REIT ETF
SPDR Series Trust: SPDR KBW Bank ETF
SPDR Series Trust: SPDR KBW Capital Markets ETF
SPDR Series Trust: SPDR KBW Insurance ETF
SPDR Series Trust: SPDR KBW Regional Banking ETF
SPDR Series Trust: SPDR Morgan Stanley Technology ETF
SPDR Series Trust: SPDR MSCI USA Quality MixETF
SPDR Series Trust: SPDR Russell 1000 Low Volatility Focus ETF
SPDR Series Trust: SPDR Russell 1000 Momentum Focus ETF
SPDR Series Trust: SPDR Russell 1000 Yield Focus ETF
SPDR Series Trust: SPDR S&P 400 Mid Cap Growth ETF
SPDR Series Trust: SPDR S&P 400 Mid Cap Value ETF
SPDR Series Trust: SPDR S&P 500 Fossil Fuel Free ETF
SPDR Series Trust: SPDR S&P 500 Growth ETF
SPDR Series Trust: SPDR S&P 500 High Dividend ETF
SPDR Series Trust: SPDR S&P 500 Value ETF
SPDR Series Trust: SPDR S&P 600 Small Cap ETF
SPDR Series Trust: SPDR S&P 600 Small Cap Value ETF
SPDR Series Trust: SPDR S&P Dividend ETF
Tidal ETF Trust: SoFi Gig Economy ETF
Transamerica ETF Trust: DeltaShares S&P 500 Managed Risk ETF
TrimTabs ETF Trust: TrimTabs Float Shrink ETF
Vanguard Admiral Funds: Vanguard S&P 500 Growth Index Fund; ETF Shares
Vanguard Admiral Funds: Vanguard S&P 500 Growth Index Fund; Institutional Shares
Vanguard Admiral Funds: Vanguard S&P 500 Value IndexFund; Institutional Shares
Vanguard Admiral Funds: Vanguard S&P 500 Value IndexFund; ETF Shares
Vanguard IndexFunds: Vanguard 500 Index Fund; Admiral Shares
Vanguard IndexFunds: Vanguard 500 Index Fund; ETF Shares
Vanguard IndexFunds: Vanguard 500 Index Fund; Institutional Select Shares
Vanguard IndexFunds: Vanguard 500 Index Fund; Investor Shares
Vanguard IndexFunds: Vanguard 500 Index Fund; Signal Shares
Vanguard Scottsdale Funds: Vanguard Russell 1000 Growth Index Fund; ETF Shares
Vanguard Scottsdale Funds: Vanguard Russell 1000 Growth Index Fund; Institutional Shares
Vanguard Scottsdale Funds: Vanguard Russell 1000 Index Fund; ETF Shares
Vanguard Scottsdale Funds: Vanguard Russell 1000 Index Fund; Institutional Shares
Vanguard Scottsdale Funds: Vanguard Russell 1000 Value IndexFund; ETF Shares
Vanguard Scottsdale Funds: Vanguard Russell 1000 Value IndexFund; Institutional Shares
Vanguard Scottsdale Funds: Vanguard Russell 2000 Growth Index Fund; ETF Shares
Vanguard Scottsdale Funds: Vanguard Russell 2000 Growth Index Fund; Institutional Shares
Vanguard Scottsdale Funds: Vanguard Russell 2000 Index Fund; ETF Shares
Vanguard Scottsdale Funds: Vanguard Russell 2000 Index Fund; Institutional Shares
Vanguard Scottsdale Funds: Vanguard Russell 2000 Value IndexFund; ETF Shares
Vanguard Scottsdale Funds: Vanguard Russell 2000 Value IndexFund; Institutional Shares
Vanguard Scottsdale Funds: Vanguard Russell 3000 Index Fund; ETF Shares
Vanguard Scottsdale Funds: Vanguard Russell 3000 Index Fund; Institutional Shares
Vanguard Wellington Fund: Vanguard US Liquidity Factor ETF
Vanguard Wellington Fund: Vanguard US Minimum Volatility ETF
Vanguard Wellington Fund: Vanguard US Momentum Factor ETF
Vanguard Wellington Fund: Vanguard US Multifactor ETF
Vanguard Wellington Fund: Vanguard US Multifactor Fund; Admiral Shares
Vanguard Wellington Fund: Vanguard US Quality Factor ETF
Vanguard Wellington Fund: Vanguard US Value Factor ETF
WisdomTree Trust: WisdomTree CBOE S&P 500 PutWrite Strategy Fund
WisdomTree Trust: WisdomTree Managed Futures Strategy Fund
WisdomTree Trust: WisdomTree Total Earnings Fund